Landscape Ecology (2006) 21:747–761
DOI 10.1007/s10980-005-5475-x

Research Article

Mapping the probability of large fire occurrence in northern Arizona, USA

Brett G. Dickson[1,2,*], John W. Prather[3], Yaguang Xu[3], Haydee M. Hampton[3], Ethan N. Aumack[3] and Thomas D. Sisk[3]
*[1]Department of Fishery and Wildlife Biology, Colorado State University, Fort Collins, CO, 80523, USA; [2]USDA Forest Service, Rocky Mountain Research Station, 2500 South Pine Knoll Drive, Flagstaff, AZ, 86001, USA; [3]Lab of Landscape Ecology and Conservation Biology, Center for Environmental Science and Education, Northern Arizona University, Flagstaff, AZ, 86011, USA; *Author for correspondence (e-mail: dickson@cnr.colostate.edu)*

Received 10 March 2005; accepted in revised form 25 November 2005

Key words: Fire risk, Lightning, Ponderosa pine, Topographic roughness, Weights of evidence, Wildland fire

Abstract

In the southwestern U.S., wildland fire frequency and area burned have steadily increased in recent decades, a pattern attributable to multiple ignition sources. To examine contributing landscape factors and patterns related to the occurrence of large ($\geqslant$20 ha in extent) fires in the forested region of northern Arizona, we assembled a database of lightning- and human-caused fires for the period 1 April to 30 September, 1986–2000. At the landscape scale, we used a weights-of-evidence approach to model and map the probability of occurrence based on all fire types ($n = 203$), and lightning-caused fires alone ($n = 136$). In total, large fires burned 101,571 ha on our study area. Fires due to lightning were more frequent and extensive than those caused by humans, although human-caused fires burned large areas during the period of our analysis. For all fires, probability of occurrence was greatest in areas of high topographic roughness and lower road density. Ponderosa pine (*Pinus ponderosa*)-dominated forest vegetation and mean annual precipitation were less important predictors. Our modeling results indicate that seasonal large fire events are a consequence of non-random patterns of occurrence, and that patterns generated by these events may affect the regional fire regime more extensively than previously thought. Identifying the factors that influence large fires will improve our ability to target resource protection efforts and manage fire risk at the landscape scale.

Introduction

Recently, the American Southwest has experienced wildland fires of relatively unprecedented size and severity (e.g., the 2000 Cerro Grande fire in New Mexico and the 2002 Rodeo-Chediski fire in Arizona). Modern fire control efforts have contributed to levels of wildland fire frequency and intensity greater than those encountered during the early part of the 20th century (Agee 1998) and atypical in the paleoecological record (Grissino-Mayer and Swetnam 2000). Beginning in the late 1800s, the landscape was dramatically altered by the introduction of domestic livestock, large-scale timber harvesting, and aggressive fire suppression activities. Today's ponderosa pine-dominated (PIPO) forests are dense with many pole-size trees that help facilitate stand-replacing crown fires

(Covington and Moore 1994). However, such extreme changes in forest structure and fire regime contribute only partially to the increased likelihood of large, natural- and human-caused fire events.

In the region that includes northern Arizona and western New Mexico, 60–70% of forest fires are ignited by lightning, compared to approximately 20% nationwide. Due to a high incidence of lightning strikes from dry thunderstorms during the summer monsoons, this area leads the nation in the average number of lightning-caused fires and average amount of National Forest area burned by these fires each year (Barrows 1978). Historically, most large fires in the Southwest were associated with broad-scale climate factors, or controls, such as El Niño-Southern Oscillation (ENSO) patterns and the persistence of drought conditions (Swetnam and Betancourt 1990; Allen 2002). However, retrospective studies of historical fire events suggest an increase in the number of large fires since the beginning of the 20th century (Swetnam 1990). For the period 1992–2003, the Southwest region (Arizona, New Mexico, and West Texas) experienced an annual average of 3059 human-caused fires and 2613 lightning-caused fires, burning an annual average of 91,906 and 84,900 ha, respectively (USDA Forest Service 2004). The increase in the size of more recent human-caused fire events may be due, in part, to an increase in the number of roads and improved access to remote forested locations (Swetnam 1990; Cardille et al. 2001; see DellaSala and Frost 2001). In spite of the risks associated with current forest conditions, more people continue to settle where dense forests interface with urban areas (Davis 1990; USDA and USDI 2000; Dombeck et al. 2004). Consequently, the number of human-caused fires is expected to rise in these areas, increasing the likelihood of stand-replacing fire events.

The importance of nonrandom patterns in fire ignition and occurrence has been recognized by recent efforts to predict these patterns at larger spatial scales (e.g., Cardille et al. 2001; de Vasconcelos et al. 2001; Díaz-Avalos et al. 2001; Preisler et al. 2004). At landscape scales (i.e., extents $>100{,}000$ ha), the probability of a large fire is associated with multiple factors including: forest type, physiographic characteristics, climate, and human activities. However, insights into the interplay among these factors and how they facilitate subsequent large fire events are poorly explored. No quantitative analyses in the Southwest have examined the spatial patterns of occurrence that led to large fires and their relationship with various landscape features. Quantifying the probability of large fire occurrence is necessary to understand: (1) the scale and periodicity of natural fire regimes (Agee 1998; Fulé et al. 2003; Malamud 2005); (2) the causes, patterns, and consequences of ecosystem-level disturbance and change (Attiwill 1994; Dale et al. 2001; McKenzie et al. 2004); (3) the socio-political implications of wildland fire and fire management (Cardille et al. 2001; Brunson and Shindler 2004; Dombeck et al. 2004); and (4) fire risk and fire threat to humans and their communities (Case et al. 2000; Keeley and Fotheringham 2001).

The objectives of this research were to: (1) assemble a geographic database of large fire events for the PIPO regions of northern Arizona; (2) broadly characterize the important landscape features of these regions that may be associated with landscape-scale patterns of fire occurrence; (3) develop predictive maps of conditional probability of occurrence for large fires over a broad spatial and temporal scale using a new and rigorous approach; and (4) quantify the relationships between fire ignition source, landscape features, and patterns of occurrence.

Methods

Study area

Our 27,065-km^2 study area included the PIPO forest regions of northern Arizona, USA (Figure 1a). Generally, these forests occurred in three distinct regions: a 3390-km^2 region that included the Kaibab Plateau to the north of the Grand Canyon; the 1418-km^2 area to the south of the Grand Canyon and northwest of Flagstaff, Arizona; and a 22,257-km^2 area that included the Mogollon Plateau, east to the New Mexico border. Common tree species on the study area also included Gambel's oak (*Quercus gambelii*), quaking aspen (*Populus tremuloides*), and other high elevation mixed-conifer species. Elevations across the study area ranged from approximately 1520 to 3840 m on Humphrey's Peak in Arizona. Because the PIPO vegetation zones typically occurred above 1520 m, we constrained the borders of our study area using this minimum elevation threshold. We also constrained the study area boundary by excluding slopes > 45°, since forest-dominated vegetation types do not usually occur in these areas. Mean annual precipitation and mean annual maximum temperature ranged from 58.7 cm and 14.3 °C, respectively, at higher elevations on the north end of the study area (Jacob Lake, 1971–2000, elev 2420 m) to 52.6 cm and 21.8 °C, respectively, at lower elevations on the south-central end of the study area (Payson Ranger Station, 1971–2000, elev 1520 m; US Western Regional Climate Center). Approximately 65% of precipitation fell as snow during the winter months (USDA Natural Resources Conservation Service).

Fire occurrence data

We compiled a digital database of federal fire occurrence data for the period 1 April to 30 September, 1986–2000. This period captures the season with the driest months in the region and monsoonal storm patterns, during which lightning strikes are most common (Swetnam and Betancourt 1998). Forest use and recreational activities are also widespread during this period. We obtained data directly from the US Departments of Agriculture and Interior, and from a national fire occurrence database (USDA Forest Service 1999). Data had a minimum resolution extent of 0.40 ha and included point-of-origin records for lightning- (LF) and human-caused fires (HF) occurring on federal lands managed by the Forest Service, Bureau of Land Management, National Park Service, Fish and Wildlife Service, and Bureau of Indian Affairs (Figure 1b). Our database did not include fire perimeter or other spatial fire spread information. We restricted our analyses to larger LF or HF (≥20 ha in extent; hereafter, we refer only to those events). We chose this threshold because fires burning beyond 20 ha are likely to be influenced more by landscape-level variables than by the immediate ignition environment. In addition, while most ignition events result in fires < 1 ha in size, those fires that do reach 20 ha are likely to grow. For example, in Colorado < 5% of fires reach 20 ha in size, but those that do have a 46% chance of reaching 100 ha and an 18% chance of reaching 400 ha in size (Neuenschwander et al. 2000). We excluded records on human-caused prescribed fires contained within planned boundaries. To avoid duplicate records in our database, we discarded an occurrence when attribute information was identical to another record within 1000 m. We converted each remaining record in the database to a point feature in a fire occurrence data layer and identified spatial coordinates using a geographic information system (GIS; ArcGIS v9.0, ESRI, Redlands, CA, USA).

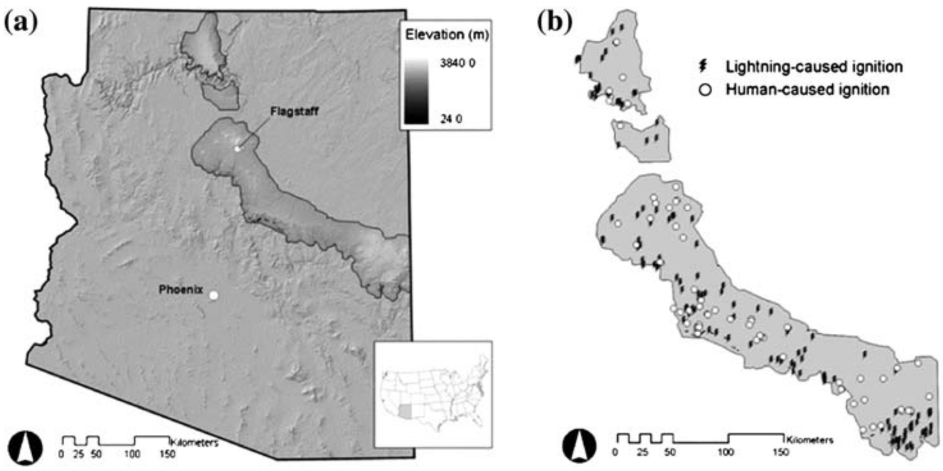

Figure 1. (a) The 27,065-km^2 study area used to examine probability of large fire occurrence. The study area included the large, PIPO forest regions of northern Arizona, USA. (b) Distribution of lightning- (n = 136) and human-caused (n = 67) large fires on the study area for the period 1 April to 30 September, 1986–2000.

Spatial input maps

We developed eight spatial data layers, or input maps, that included information on physiographic, biotic, climatic, spatial, and human factors that were likely to influence the probability of fire occurrence. Specifically, we created unique input maps for elevation, slope, aspect score, topographic roughness, PIPO vegetation, precipitation, road density, and spatial domain (Figures 1a and 2; see methods below). Because our analytical approach (weights of evidence, see below) required categorical, rather than continuous, input data, we categorized all input maps, with the exception of topographic roughness and spatial domain, into two classes: high and low. The thresholds for each class, or category, were determined by quantile cutoffs based on landscape area. Thus, each category covered an equal proportion of the landscape and the final number of categories in the topographic roughness map was determined by optimizing the maximum number of categories with significant contrast values in a weights-of-evidence analysis (see below; Bonham-Carter et al. 1989). To avoid 'data dredging,' we limited our search to categories that could be identified using the quantile classification method.

We used the Spatial Analyst extension to ArcGIS to derive the elevation, slope, aspect, and topographic roughness maps based on a 30-m US Geological Survey (USGS) digital elevation model mosaic resampled (continuous) to a 90-m resolution. For elevation (range = 1520.0–3840.0 m) and slope (range = 0.0–45.0°), the value of each 1-km^2 cell in the final map was calculated as the mean value of all 90-m cells contained within that 1-km^2 cell (see Figure 1a for elevation map). For aspect, we assigned each 90-m cell an 'aspect score' value based on that cells relationship with the regional prevailing wind direction in the fire season (225.0° or SW); cells with aspects between 195.0° and 255.0° were assigned a value of two, cells between 135.0° and 195.0°, or between 255.0° and 315.0°, a value of one, and all other cells were assigned a value of zero. The final aspect score value for each 1-km^2 cell was the sum of all 90-m cell scores contained within that cell (Figure 2a). To derive our terrain roughness map, we calculated the standard deviation for the elevation of all 90-m cells in a 3×3 neighborhood. The final value for each 1-km^2 cell was determined by summing the standard deviation values of all 90-m cells within that cell (Figure 2b). Low to high class numbers indicate lower to higher degrees of topographic roughness.

Because different forest types have fire regimes that differ in frequency and intensity (Swetnam and Baisan 1996), it was necessary to develop an input map of dominant forest vegetation on our study area. We first obtained a 30-m resolution land cover map from the USGS National Land Cover Dataset (1992). Since this map represents only a coarse classification of dominant forest types (e.g., evergreen forest), we supplemented this map with Enhanced Thematic Mapper (ETM; 30-m resolution) satellite imagery data for the study region. Our final forest vegetation input map was a binary map that classified areas as PIPO or non-PIPO forest (Figure 2c). The value for each 1-km^2 cell used in our analyses was determined by resampling all original 30-m cells within that cell.

To assess the influence of climate on fire occurrence, we obtained a 1-km resolution grid representing mean annual precipitation (range = 22.9–107.1 cm, mean = 59.5) over the period 1980–1997 (from Daymet US climate model data center; see Thornton et al. 1997; Figure 2d). We did not incorporate information on other climatic variables (e.g., temperature, relative humidity, or insolation) because correlations between these variables and fire occurrence are less strong, and because large fires in the Southwest are strongly linked to rainfall patterns (Swetnam and Betancourt 1990, 1998).

To represent patterns of human-use and access on the study area, we used year 2000 US Census Bureau TIGER (Topologically Integrated Geographic Encoding and Referencing) road files to develop a grid-based map of road density (km/km^2; range = 0.0–19.8, mean = 2.3) using a simple density operation in the ArcGIS Spatial Analyst (Figure 2e).

To determine if occurrences of fire were influenced by spatial location, we developed a simple input map using six spatial domains (Figure 2f). These arbitrary domains were equal in shape and extent and did not capture equal-area proportions of the study area. We also tested the hypothesis of complete spatial randomness in the occurrence data by buffering our study area to 10 km and using an edge corrected point pattern analysis (R = test statistic, α = 0.05; see Clark and Evans 1954; Bailey and Gatrell 1995).

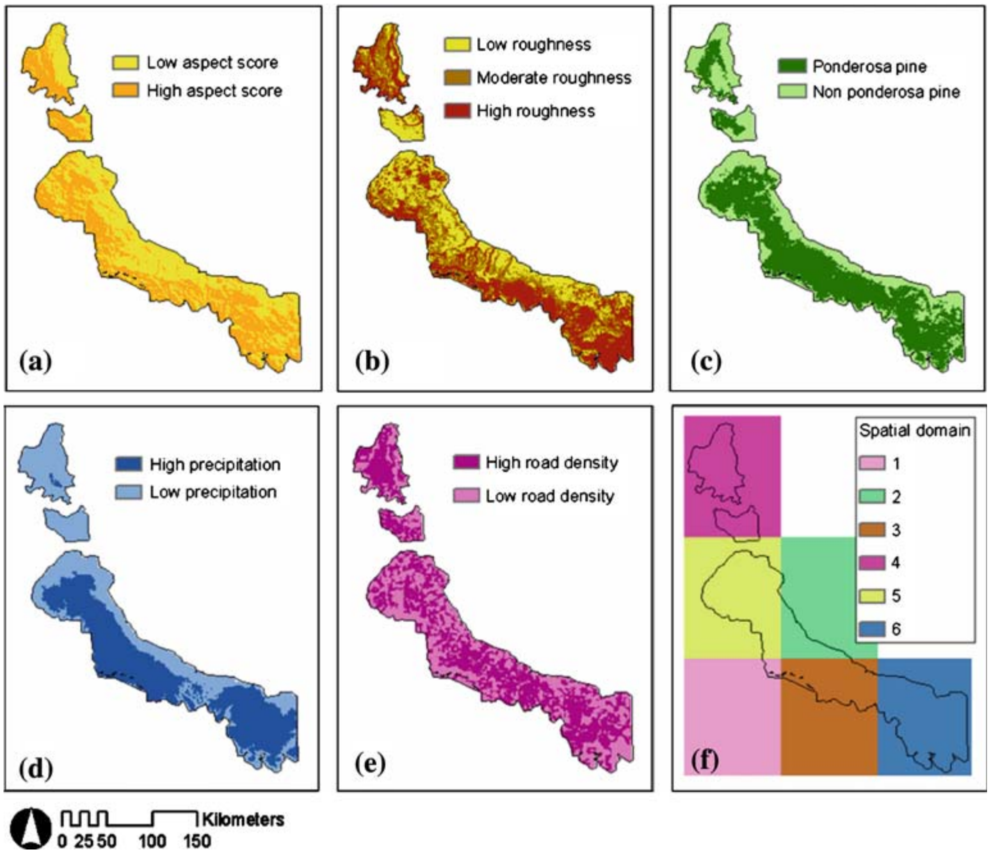

Figure 2. Spatial input maps used in the analyses of large fires in northern Arizona. Input maps for (a) aspect score; (b) topographic roughness; (c) forest type; (d) precipitation; (e) road density; and (f) spatial domain are shown.

Weights-of-evidence modeling

We used weights-of-evidence (WOE) modeling, a Bayesian method of event prediction, to quantify fire occurrence probability. We chose this method because it explicitly considers the spatial association between fire occurrence and input map data (i.e., it is 'spatially explicit'), is robust to small sample sizes at large spatial scales, and is easy to implement and interpret using categorical data. Moreover, unlike traditional approaches, the method does not rely on assumptions of normality in the input map distributions and can be informed by a known prior distribution of empirical data. The approach was originally used in medical diagnoses (e.g., Spiegelhalter 1986), but has recently been extended to the prediction and spatial analysis of mineral deposits (Agterberg 1989; Raines and Mihalasky 2002), fossilized packrat middens (Mensing et al. 2000), and plant migrations (Lyford et al. 2003). WOE models use the spatial location of known occurrence points to determine coefficients for a set of categorical input maps (Bonham-Carter et al. 1989). For each analysis unit, or unit cell, these coefficients represent the conditional probability of the input map pattern being: (a) present with a known occurrence (e.g., a large fire); (b) present without an occurrence; (c) absent with an occurrence; or (d) absent without an occurrence. The WOE model takes a log-linear form, and the final output is a posterior probability map showing the conditional probability for presence of an occurrence at each unit cell.

Following the procedure described by Bonham-Carter et al. (1989), steps in our WOE analysis included: (1) *a priori* selection of input maps likely to be useful in prediction of fire occurrence; (2) estimation of a prior probability for the study area given only the known occurrence data; (3)

identification of an optimal classification scheme for the input maps and use of conditional probability ratios to calculate weights of evidence for each input map; (4) a pairwise test of conditional independence for each of the input maps, with respect to the known fire occurrences (test statistic $=\chi^2$, $\alpha = 0.01$), combining maps when the conditional assumption was violated; (5) combining the input map weights calculated in step 2; and (6) creating a new map of conditional posterior probability and estimate of prediction uncertainty for the final input maps correlated with fire occurrence.

For all unit cells where a fire occurred, $N(D)$, and given the total number of cells on our study area, $N(T)$, we computed the prior probability, $P(D)$, of occurrence as

$$P(D) = \frac{N(D)}{N(T)}.$$

Expressed as odds (O), we computed the prior probability that a randomly selected cell contained a fire by

$$O(D) = \frac{P(D)}{P(\overline{D})},$$

where $P(\overline{D})$ is the prior probability that a fire did not occur in that cell. Given a set of evidence, E_i, where $i = 1, 2, \ldots, n$, and n is the total number of input maps, where each represents an independent predictor variable, the conditional posterior probability, $P(D|E_i)$, was expressed as odds by

$$O(D|E_i) = O(D)\frac{P(D|E_i)}{P(\overline{D}|E_i)}.$$

According to the above equations and Bayes' rule, and assuming conditional independence in the input maps (Bonham-Carter et al. 1989), the following equations can be derived

$$O(D|E_i) = O(D)\frac{P(E_i|D)}{P(E_i|\overline{D})},$$

and

$$\mathrm{Ln}(O(D|E)) = \mathrm{Ln}(O(D)) + \mathrm{Ln}\left(\frac{P(E_1|D)}{P(E_1|\overline{D})}\right) + \cdots + \mathrm{Ln}\left(\frac{P(E_n|D)}{P(E_n|\overline{D})}\right).$$

The weight, W_i, for evidence pattern, i, is defined by the expression

$$\mathrm{Ln}\left(\frac{P(E_i|D)}{P(E_i|\overline{D})}\right).$$

Thus, if E_i is present, the weight, where $j = 1, 2, \ldots, n$, and n is the total number of input maps, is

$$W_j^+ = \mathrm{Ln}\left(\frac{P(E_i|D)}{P(E_i|\overline{D})}\right),$$

and if E_i is absent, the weight is

$$W_j^- = \mathrm{Ln}\left(\frac{P(\overline{E_i}|D)}{P(\overline{E_i}|\overline{D})}\right).$$

Therefore, the log odds of a unit cell's posterior probability can be obtained by adding weights W^+ or W^- for presence or absence of each input map unit cell to the log odds of the prior probability, W_0, expressed as

$$\begin{aligned}\mathrm{Ln}(O(D|E_i)) &= W_0 + W_1^+(\text{or } W_1^-) + \cdots \\ &\quad + W_n^+(\text{or } W_n^-) \\ &= \sum_{j=0}^{n} W_j^k,\end{aligned}$$

where k represents a positive (presence) or negative (absence) weight. Finally, the unit cell posterior probability, $P(D|\ E_i)$, is obtained from the logit equation

$$P(D|E_i) = \frac{\exp \mathrm{Ln}(O(D|E_i)))}{1 + \exp \mathrm{Ln}(O(D|E_i)))}$$

allowing for easier interpretation of the weights. When an input map pattern was correlated with known occurrences, the contrast

$$C = W_j^+ - W_j^-$$

provided a measure of the strength of this correlation. A positive or negative value (range between $+2$ and -2) for C indicated a positive or negative spatial correlation, respectively. We ranked the relative importance of each input map according to the value for C. We considered absolute values for $C \geq 0.30$ to represent more meaningful contrasts. To test whether the contrast value for each individual input map was sufficiently different from 0 (no correlation), we calculated a 'studentized' contrast value (test statistic = student(c), $\alpha = 0.05$; Bonham-Carter et al. 1989). For each WOE analysis, the weights from each of the overlapping input maps with statistically significant studentized contrast values were summed, resulting in an output map representing an integrated pattern of posterior conditional probabilities.

To assess uncertainties associated with our posterior probability maps, we estimated the total uncertainty (Bonham-Carter et al. 1989) as the variance in the weights, combined with the variance for any missing cell values in the overlapping input maps. Uncertainties due to differences in the weights of overlapping input maps were calculated as

$$\sigma^2 P_{post} = \left[\sigma^2 \sum_{j=1}^{n} \sigma^2 W_j^k\right] \cdot P_{post}^2.$$

Uncertainties due to missing or incomplete values in the overlapping input maps were calculated as

$$\sigma_j^2(P_{post}) = \{P(D|E_i) - P(D)\}^2 P(E_i) + \{P(D|\overline{E_i}) - P(D)\}^2 P(\overline{E_i}).$$

Total uncertainty in the posterior probability maps was estimated as

$$\sigma^2(TOTAL) = \sigma^2(WEIGHTS) + \sum_{j=1}^{n} \sigma_j^2(MISSING).$$

For the final uncertainty maps, we calculated a studentized uncertainty statistic for each cell as

$$\frac{P_{post}}{\sigma_{TOTAL}}.$$

Values of this ratio < 1.960 represented cells with significant uncertainty ($\alpha = 0.05$; Bonham-Carter et al. 1989).

We used the Arc-SDM (Kemp et al. 2001) spatial data modeler extension to ArcView v3.3 (ESRI, Redlands, CA, USA) to conduct all WOE analyses. We modeled all fire (AF) types (LF and HF combined), and then we modeled LF alone. Because too few (< 100) records for HF were present in our final database, we did not model these occurrences separately. We report all probability and uncertainty values per 1-km^2 cell for our period of study.

Results

Fire occurrence

Between 1 April and 30 September, 1986–2000, 203 fires occurred on our study area (Figure 1b) and burned 101,751 ha. Of this total, 136 (67%) were LF and most (71%, $n = 97$) of these burned a total area $\leqslant$200 ha per year. LF burned more than 4 times the area burned by HF (83,055 vs. 18,696 ha). The greatest number of fires occurred in 2000 ($n = 26$) and the highest amount of total annual area burned in 1996 (38,140 ha). Of this total area, 32,674 ha (86%) burned as a result of LF. The highest annual amount of average area burned also occurred in 1996 (2119 ha, SD = 3831, $n = 18$). HF burned the most area in 2000 (total = 6422, mean = 2141, $n = 3$).

The spatial distribution of fire occurrences on our study area was significantly nonrandom for AF ($R = 0.704$, $z = -8.805$, $p < 0.001$, $n = 242$) and for LF alone ($R = 0.683$, $z = -7.687$, $p < 0.001$, $n = 161$).

Probability modeling

Spatial input maps for slope and topographic roughness were highly correlated (correlation coefficient = 0.87), leading us to drop slope and consider seven input maps in our WOE models. As might be expected for this region, mean annual precipitation and elevation were weakly correlated (correlation coefficient = 0.30), as were precipitation and topographic roughness (0.26). We did not consider these correlations sufficient to drop these input maps from subsequent analyses. The pairwise test of the assumption of conditional independence for the PIPO forest and precipitation input maps was not satisfied in the analysis of AF ($\chi^2 = 41.6$, $p > 0.01$, d.f. = 2). Therefore, we combined these maps (Bonham-Carter et al. 1989; Agterberg and Cheng 2002) and evaluated a new input map (Forest_Precip) with two binary classes: presence of PIPO forest or high precipitation (class 1; 69% of study area) and absence of both (class 2; 31% of study area). New tests for all of the input maps satisfied the conditional independence assumption.

The prior probability of AF was 0.008. At the resolution and extent (spatial and temporal) of our input maps, the AF posterior probability was most influenced by topographic roughness, followed by road density, and Forest_Precip (Table 1). Elevation, aspect, and spatial domain were not important predictors of occurrence in this model ($C < 0.30$, $p > 0.05$). For this analysis, we identified three topographic roughness classes for which absolute contrast values were ≥0.30 and statistically significant. High topographic roughness was the best predictor of AF occurrence ($C = 0.912$), and was also characterized by the highest positive weight ($W^{+} = 0.511$). Low road density and Forest_Precip were also good predictors. Areas of moderate ($C = -0.538$) and low ($C = -0.572$) topographic roughness were also considered important predictors of where AF were unlikely to occur.

Our WOE model for AF summed the weights of the topographic roughness, road density, and Forest_Precip maps. The posterior probability of a fire occurrence ranged between 0.012 and 0.074 (mean = 0.031, SD = 0.016; Figure 3a). The corresponding uncertainty for these conditional probabilities ranged between 0.003 and 0.021 (mean = 0.008, SD = 0.004). Because of the relatively large number of occurrences in our WOE analysis of AF, our use of statistically significant input maps, and few missing data in our overlapping input maps, total uncertainty was minimized (Figure 3b). No cells had studentized uncertainty values < 1.960.

The prior probability for LF was 0.005. Our tests of the conditional independence assumptions for the input maps in the LF analysis were satisfied using the topographic roughness, road density, forest vegetation, and aspect score input maps. Posterior probability of LF was most influenced by topographic roughness, followed by road density, PIPO forest, and aspect (Table 2). Precipitation, elevation, and spatial domain were not significant predictors. For LF, we again identified three topographic roughness classes for which contrast values were > 0.30. High topographic roughness was the most important ($C = 1.246$) predictor. Cells with highest values also had the largest positive weight ($W^{+} = 0.647$). Low road density and PIPO forest were better predictors of occurrence than high aspect score. Areas with the lowest values for topographic roughness were important ($C = -1.045$) predictors of where LF were unlikely to occur.

For our WOE model of LF, we summed the weights for the topographic roughness, road density, forest vegetation, and aspect score input maps. The posterior probability of a fire due to LF ranged between 0.003 and 0.078 (mean = 0.018, SD = 0.017; Figure 3c). The corresponding total uncertainty for these conditional probabilities ranged between 0.001 and 0.021 (mean = 0.006, SD = 0.005). Compared to the analysis using AF, fewer occurrences in the WOE analysis of LF provided for greater uncertainty in more cells (Figure 3d). However, very few ($n = 34$) cells had studentized uncertainty values < 1.960.

Discussion

Fire occurrence

Consistent with an earlier figure reported by Barrows (1978) for all natural-caused fires, we found

Table 1. Input maps significantly correlated with the occurrence of all ($n = 203$) large fires on the study area, and their associated WOE statistics, for the period 1 April to 30 September, 1986–2000.

Input map	Class	No. of occurrences	W^{+}	SD (W^{+})	W^{-}	SD (W^{-})	Contrast (C)	SD (C)	student(c)*
Roughness	High	112	0.511	0.095	−0.401	0.105	0.912	0.142	6.435
Road density	Low	118	0.244	0.093	−0.263	0.109	0.507	0.143	3.552
Forest_Precip	1	153	0.091	0.081	−0.240	0.143	0.332	0.165	2.014
Roughness	Moderate	47	−0.385	0.146	0.153	0.080	−0.538	0.167	−3.221
Roughness	Low	44	−0.417	0.151	0.155	0.080	−0.572	0.171	−3.345

Because of the inverse relationship between binary value input map classes, we report only those class results for which values of C were positive. Input map importance in predicting large fire occurrence is ranked from top (high) to bottom (low) according to the value of C. Forest_Precip class 1 indicates presence of PIPO forest or high precipitation.
*Values statistically significant at $\alpha = 0.05$ (> 1.96, < −1.96).

that 67% of all fires on our study area were LF. However, a relatively small number of these fires represented a substantial fraction of the total annual area burned during our period of study. Even though they occurred infrequently, HF burned extremely large areas. For example, a human-ignited prescribed fire in Grand Canyon National Park in 2002 escaped its boundary and consumed 6243 ha, or 97% of the total area burned due to human causes in that year (33% of the period total). In June of 2002 the Rodeo-Chediski fire, the largest recorded fire in Arizona state history, was human ignited and burned approximately 187,000 ha within our study area.

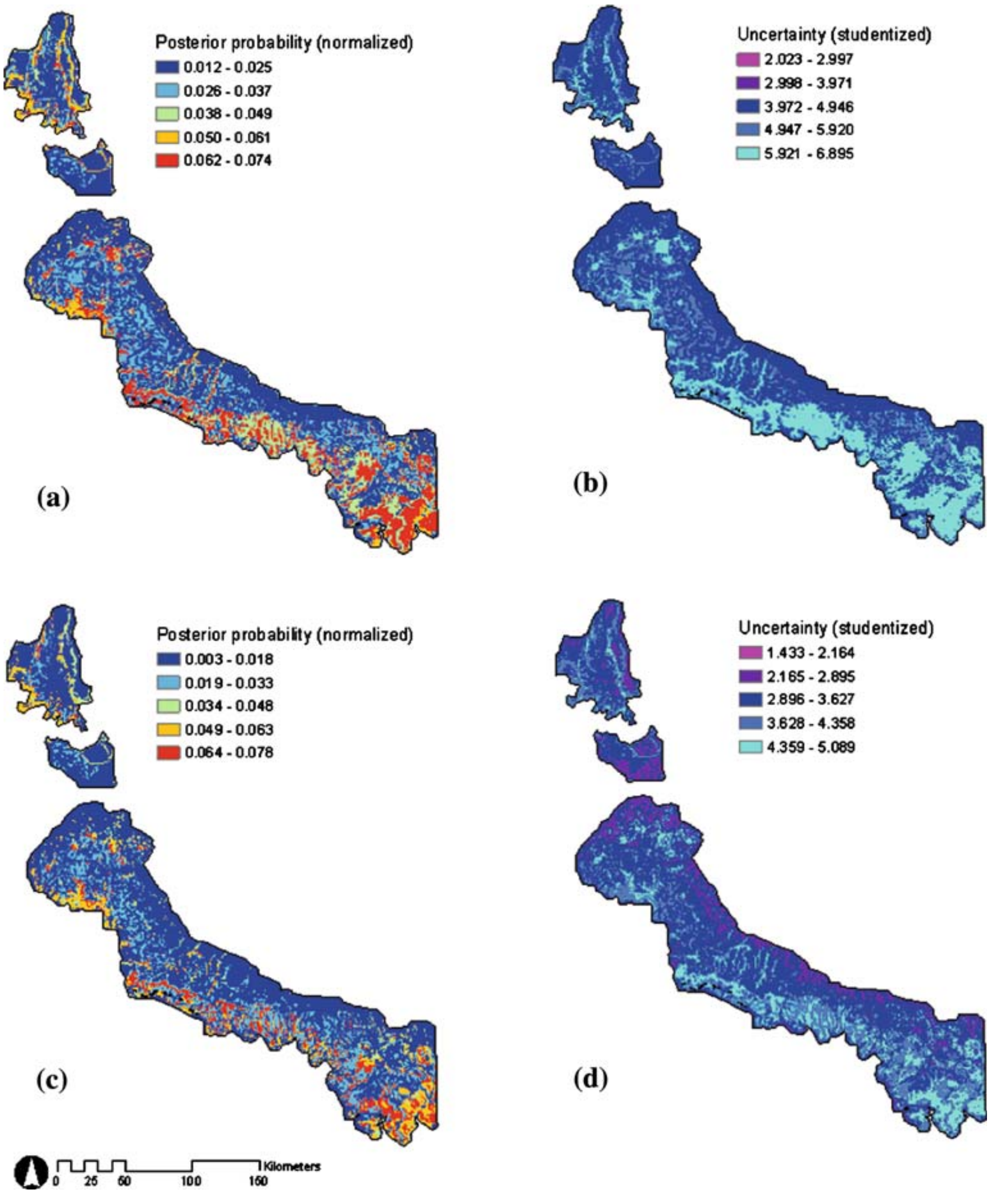

Figure 3. (a) Normalized posterior probability of occurrence and (b) studentized uncertainty values for all (n = 203) large fire types on the study area. (c) Normalized posterior probability of occurrence and (d) studentized uncertainty values for lightning-caused (n = 136) large fires on the study area. Lower studentized uncertainty values indicate greater uncertainty and values < 1.960 are not statistically different from zero. Ranges for all values are scaled using an equal interval classification.

Table 2. Input maps significantly correlated with the occurrence of lightning-caused ($n = 136$) large fires on the study area, and their associated WOE statistics, for the period 1 April to 30 September, 1986–2000.

Input map	Class	No. of occurrences	W^+	SD (W^+)	W^-	SD (W^-)	Contrast (C)	SD (C)	student(c)*
Roughness	High	86	0.647	0.108	−0.599	0.142	1.246	0.178	6.988
Road density	Low	91	0.385	0.105	−0.499	0.149	0.884	0.183	4.839
Forest vegetation	PIPO	96	0.182	0.102	−0.337	0.158	0.519	0.189	2.752
Aspect score	High	83	0.155	0.110	−0.203	0.138	0.358	0.176	2.030
Roughness	Moderate	30	−0.433	0.182	0.166	0.097	−0.599	0.207	−2.891
Roughness	Low	20	−0.805	0.224	0.240	0.093	−1.045	0.243	−4.310

Because of the inverse relationship between binary value input map classes, we report only those class results for which values of C were positive. Input map importance in predicting large fire ignition occurrence is ranked from top (high) to bottom (low) according to the value of C.
*Values statistically significant at $\alpha = 0.05$ (>1.96, <-1.96).

Probability modeling

We identified significant interactions between landscape features and landscape-scale patterns of fire occurrence. Predictors differed by analysis (LF vs. AF), although highly ranked predictors were similar for both WOE analyses. For the most important predictors, we observed higher contrast values and weights for LF than for AF. Patterns observed in our analysis of AF were likely dampened by the inclusion of HF, which were highly variable in their timing, location, and extent. Additionally, because our analyses considered only one anthropogenic input map (road density), we were unable to account for the range of unique factors that likely influence patterns of HF (e.g., proximity to urban centers, human density). A qualitative examination of patterns for AF revealed that HF are more likely to occur in areas of high road density and LF in areas of low road density.

For the 15-year period we analyzed, the maximum conditional posterior probability value for each of our WOE analyses was not large: 0.078 for LF and 0.074 for AF. However, compared with their prior probabilities, these maximum values yield odds ratios of ~10:1 for AF and ~16:1 for LF. Because we were unable to include important fire behavior variables in our WOE analyses we believe that the maximum probability of a fire is higher than we estimated. For example, accurate input maps for fuel type and fuel load were unavailable at the temporal and spatial extent of our analyses. Temporal variability in fuel moisture, humidity, wind speed, and other factors that are difficult to incorporate into spatial models, will also result in variability in the occurrence of large fires. Nevertheless, we believe our posterior probability estimates capture the statistical and ecological importance of the input maps included in the WOE analyses.

Topographic roughness was an important landscape feature in predicting the occurrence of fire, a result not previously demonstrated at the landscape scale for the Southwest. Guyette and Dey (2000) identified topographic roughness as one of the most important and temporally persistent landscape variables in their assessment of fire frequency in the Ozark Mountains of southeastern Missouri. The interaction between topography and fire behavior is a complex process mediated by the influence of local climate, vegetation, and the spatial distribution of fuels (Whelan 1995). Topographically complex areas can facilitate or impede fire occurrence and behavior (Whelan 1995; Graham et al. 2004). Moreover, rate of spread may increase with steeper slopes because flames are angled closer to the ground and because the process of heat convection within the fire produces supplemental wind effects (Whelan 1995; DeBano et al. 1998).

Fire suppression efforts in areas of remote and rough terrain can be constrained by slower reporting and response times and limited access. The observed relationship between high topographic roughness and the posterior probability of fire occurrence may be influenced by this circumstance. Although the road density and topographic roughness input maps were not correlated (correlation coefficient = 0.04), areas with lower road densities were highly ranked by each WOE analysis. For either LF or HF, areas with lower road densities may place fewer artificial fuel breaks in the path of an expanding fire event. If larger fires occur in rugged areas with lower road densities, then the role of limited road access for suppression efforts, for example, should be recognized in the management of the present fire regime. This is not to suggest, however, that fire occurrence could be reduced by the construction of new roads in fire-prone areas; more roads in these areas will allow increased access by humans, which is likely to result in an increase in HF (Swetnam 1990; Brown et al. 2004). In the upper Midwest, where most fires are human-caused, the probability of occurrence of a larger fire has been found to be positively correlated with road density (Cardille et al. 2001), and in the San Jacinto mountains of California, fires are more likely to occur near roads (Chou et al. 1993). An increase in HF could offset the ecological benefits of fires due to LF, or the perceived benefits of fire suppression activities in remote areas. Additionally, road building can promote resource erosion and degradation (see Grigal 2000; DellaSala and Frost 2001), increase invasion by exotic species (Forman 2000; Gelbard and Belnap 2003), and fragment habitats (Reed et al. 1996; McGarigal et al. 2001).

We were unable to identify the specific mechanisms underlying the significant relationship between PIPO forest and increased probability of fire occurrence. However, previous research in the region has identified a number of possible factors including a recent and rapid accumulation of forest-floor fuels (Sackett and Haase 1996), tree densities surpassing historic levels (Covington and Moore 1994), reduced tree vigor (Covington et al. 1997), and increases in the incidence of tree mortality agents, such as bark beetles and dwarf mistletoes (see Dahms and Geils 1997). These factors have likely been exacerbated by intensive livestock grazing, timber harvesting, and fire suppression activities (Covington and Moore 1994). Moreover, increased human use of the PIPO forest type, primarily in the form of recreation activities and development (see Dahms and Geils 1997), could further modify the forested landscape in ways that facilitate large fire events.

Areas with high precipitation did not rank as a dominant influence on AF patterns. The coarse resolution (spatial and temporal) of our precipitation input map may have resulted in low power to detect relationships. In the Southwest, lightning strikes and high levels of precipitation are often significantly positively correlated (Gosz et al. 1995). However, our results indicate that LF were not correlated with precipitation during the period of our analysis. On our study area, high levels of precipitation likely contribute to increased fuels in PIPO stands. For example, Swetnam and Betancourt (1998) identified a strong relationship between the recent growth of southwestern trees and exceptionally high amounts of annual precipitation since 1976. In response to a dry period that follows a sequence of extremely wet seasons, accumulated fuels can contribute to exceptionally large fire events (Swetnam and Betancourt 1998; Grissino-Mayer and Swetnam 2000). Because our occurrence data span a period of 15 years, the role of longer-term patterns of climatic oscillation (e.g., ENSO) and periodic drought is not well represented by our analysis and interpretation. Nevertheless, many of the major controlling factors in our models are topographic in nature (roughness, aspect), and these may be more important in determining local patterns of fires than climatic effects, which are likely to affect the entire region in a similar fashion.

In our WOE analysis of LF, aspect score was not a highly ranked predictor variable. Areas with aspects facing the prevailing wind direction (generally, south-southwest) were significantly related with LF. The more open stands and lower tree densities that tend to occur on these aspects permit higher wind speeds (Weatherspoon 1996). Combined with higher amounts of solar radiation, this factor often facilitates more rapid drying of surface and standing fuels (Weatherspoon 1996) and increase probability of ignition (Graham et al. 2004). Our results suggest that aspect score, based on prevailing wind direction, captures important landscape features related to large fire occurrence.

Elevation was not highly correlated with the regional occurrence of fire. Although we constrained our analyses to include only those fires above 1520 m, our study area included a wide elevation range (2320 m). Previous research in other regions of the West has identified relationships between LF and elevation (Vankat 1985; van Wagtendonk 1991; Díaz-Avalos et al. 2001; Fulé et al. 2003). These studies, however, evaluated the frequency of fire events of any detectable size. Similar to our results, Preisler et al. (2004) concluded that elevation was not a significant predictor of an ignition turning into a large fire in Oregon, and in the Pacific Northwest, Heyerdahl et al. (2001) concluded elevation was not a primary control of the fire regime at the regional scale.

The number of fires in each spatial domain provided insufficient evidence for coarse-scale, spatial clustering of these events. At a regional scale, Díaz-Avalos et al. (2001) and Preisler et al. (2004) each identified the importance of spatial location in estimating the probability of ignition occurrence in Oregon. However, our more coarse method of characterizing spatial location in the WOE models was unable to detect a statistically similar pattern. Apparent clustering of LF in the southeastern domain occurred in the most rugged, remote, and lightly populated subregion of the study area. Thus, factors such as the time lag in suppression efforts due to delays in reporting and response may result in a larger number of fires than in other subregions.

The nonrandom distribution of fire occurrence on our study area indicated localized patterns of spatial clustering in these events. On average, the nearest-neighbor distance between AF and LF types was 4 km and 5 km, respectively. Using point pattern analysis, Podur et al. (2003) also detected significant local-scale clustering in lightning strikes in Ontario and determined these patterns to be principally related to localized phenomena. Our results suggest that event clustering was a function of local-scale factors and that occurrence should be modeled as a multi-scale process.

Management and research implications

Our results indicate that seasonal fire events at the landscape scale were a consequence of nonrandom patterns of occurrence, and that these patterns are significantly related to environmental factors. The occurrence pattern of fires on our study area was not strongly associated with precipitation. 'Top–down' influences (*sensu* Heyerdahl et al. 2001), such as those exerted by regional climatic patterns at human time scales, may not currently affect the regional fire regime to the extent they did historically. Instead, topographic roughness, combined with reduced access to these areas, appear to be significant controls (the 'bottom–up' controls posited by Heyerdahl et al. 2001) on the present fire regime in this region.

Forest fuels reduction and restoration treatments can be important in managing the threat of fire to communities and resources (Covington 2000). Locating these treatments in remote and rugged areas is strategically difficult and prescribed fires in more accessible locations appears to be a reasonable management alternative so long as human communities are protected (Allen et al. 2002; Dombeck et al. 2004). However, fire behavior and the restoration of fire regimes in these locations deserves greater research attention. Recent research has assessed the potential to minimize fire threat to populated areas by strategically placing forest treatments and fuel breaks around communities (see Graham et al. 2004). Our results suggest that treatments intended to reduce fire threat around communities should first target areas bordering rough terrain, thus providing a fuel break in areas where fires are more likely to spread. Because fires tend to ignite in rugged and remote areas, fire suppression efforts in neighboring populated areas should be evaluated in the context of public acceptance of fire as a natural disturbance process.

Using a Bayesian framework, Díaz-Avalos et al. (2001) also quantified the influence of spatial and environmental risk factors on the regional probability of fire occurrence. Like Díaz-Avalos et al. (2001), our novel and spatially explicit methods provide a tractable approach to modeling probability of fire occurrence, and our map outputs can be useful in the planning and coordination of community and/or regional efforts to identify areas at greatest risk. Currently, our WOE models are being used to develop maps of fire risk on an 800,000-ha landscape in northern Arizona and to model priority areas for landscape-level treatments (Sisk et al. In press). We agree with Prestemon et al. (2002) that an improved understanding of fire risk must integrate patterns of human activity, and that continued research is needed to assess wildfire-risk factors and damage-reduction strategies. Often, fuel loadings are the only characteristic taken into account when planning management actions to reduce fire threat. Moreover, it is our experience that fire managers often believe that locations where large fires are likely to start cannot be identified spatially. However, fires require not only fuels, but ignition sources and conditions that promote fire spread. While fuels reduction is important in managing fire risk, treatments designed to reduce fuels may do little to reduce fire threat if they are not strategically placed in or around areas where large fire events are most likely to occur. Insights to the patterns of fire risk, in terms of landscape attributes, will increase our ability to assess and manage fire threat. In addition, knowledge of occurrence patterns will accelerate restoration efforts, particularly when natural fire is a component of the restoration prescription.

Acknowledgements

We thank A. B. Franklin, R. M. King, B. R. Noon, W. H. Romme, D. M. Theobald and two anonymous reviewers for comments on an earlier draft of the manuscript. This research was supported by the Forest Ecosystem Restoration Assessment (ForestERA) project, funded by the Ecological Research Institute at Northern Arizona University, and the USDA Forest Service, Rocky Mountain Research Station research work unit numbers RMRS-4156 and RMRS-4852.

References

Agee J.K. 1998. The landscape ecology of western forest fire regimes. Northwest Sci. 72: 24–34.

Agterberg F.P. 1989. Computer programs for mineral exploration. Science 245: 76–81.

Agterberg F.P. and Cheng Q. 2002. Conditional independence test for weights-of-evidence modeling. Nat. Resour. Res. 11: 249–255.

Allen C.D. 2002. Lots of lightning and plenty of people: An ecological history of fire in the upland Southwest. In: Vale T.R. (ed.), Fire, Native Peoples, and the Natural Landscape. Island Press, Covelo, CA, USA, pp. 143–193.

Allen C.D., Savage M., Falk D.A., Suckling K.F., Swetnam T.W., Schulke T., Stacey P.B., Morgan P., Hoffman M. and Klingel J.T. 2002. Ecological restoration of southwestern ponderosa pine ecosystems: a broad perspective. Ecol. Appl. 12: 1418–1433.

Attiwill P.M. 1994. The disturbance of forest ecosystems: the ecological basis for conservative management. Forest Ecol. Manage. 63: 247–300.

Bailey T.C. and Gatrell A.C. 1995. Interactive Spatial Data Analysis. Longman Group Limited, Essex, UK.

Barrows J.S. 1978. Lightning fires in southwestern forests. Final Report to USDA Forest Service, Intermountain Forest and Range Experiment Station. Cooperative Agreement 16-568-CA. Fort Collins, CO, USA.

Bonham-Carter G.F., Agterberg F.P. and Wright D.F. 1989. Weights of evidence modelling: a new approach to mapping mineral potential. In: Agterberg F.P and Bonham-Carter G.F. (eds), Statistical Applications in the Earth Sciences. Geological Survey of Canada paper 89-9, Ottawa, Ontario, Canada, pp. 171–183.

Brown R.T., Agee J.K. and Franklin J.F. 2004. Forest restoration and fire: principles in the context of place. Conserv. Biol. 18: 903–912.

Brunson M.W. and Shindler B.A. 2004. Geographic variation in social acceptability of wildland fuels management in the western United States. Soc. Nat. Resour. 17: 661–678.

Cardille J.A., Ventura S.J. and Turner M.G. 2001. Environmental and social factors influencing wildfires in the Upper Midwest, United States. Ecol. Appl. 11: 111–127.

Case P., Banks B., Butler E. and Gosnell R. 2000. Assessing potential wildfire effects on people. In: Sampson R.N., Atkinson R.D. and Lewis J.W. (eds), Mapping Wildfire Hazards and Risks. The Haworth Press, New York, NY, USA, pp. 159–176.

Chou Y.H., Minnich R.A. and Chase R.A. 1993. Mapping probability of fire occurrence in the San Jacinto Mountains, California. Environ. Manage. 17: 129–140.

Clark P.J. and Evans F.C. 1954. Distance to nearest neighbor as a measure of spatial relationships in populations. Ecology 35: 445–453.

Covington W.W. 2000. Helping western forests heal: the prognosis is poor for U.S. forest ecosystems. Nature 408: 135–136.

Covington W.W., Fulé P.Z., Moore M.M., Hart S.C., Kolb T.E., Sackett J.N. and Wagner M.R. 1997. Restoring ecosystem health in ponderosa pine forests of the Southwest. J. Forest. 95: 23–29.

Covington W.W. and Moore M.M. 1994. Southwestern ponderosa forest structure and resource conditions: changes since Euro-American settlement. J. Forest. 92: 39–47.

Dahms C.W. and Geils B.W. (eds) 1997. An assessment of forest ecosystem health in the Southwest. USDA Forest Service General Technical Report RM-GTR-295. Fort Collins, CO, USA.

Dale V.H., Joyce L.A., McNulty S., Neilson R.P., Ayres M.P., Flannigan M.D., Hanson P.J., Irland L.C., Lugo A.E., Peterson C.J., Simberloff D., Swanson F.J., Stocks B.J. and Wotton B.M. 2001. Climate change and forest disturbances. BioScience 51: 723–734.

Davis J.B. 1990. The wildland-urban interface: paradise or battleground. J. Forest. 88: 26–31.

DeBano L.F., Neary D.G. and Ffolliott P.F. 1998. Fire's Effects on Ecosystems. John Wiley and Sons, New York, NY, USA.

DellaSala D.A. and Frost E. 2001. An ecologically based strategy for fire and fuels management in national forest roadless areas. Fire Manage. Today 61: 12–23.

de Vasconcelos M.J.P., Silva S., Tomé M., Alvim M. and Pereira J.M.C. 2001. Spatial prediction of fire ignition probabilities: comparing logistic regression and neural networks. Photogramm. Eng. Remote Sens. 67: 73–81.

Díaz-Avalos C., Peterson D.L., Alvarado E., Ferguson S.A. and Besag J.E. 2001. Space–time modelling of lightning-caused ignitions in the Blue Mountains, Oregon. Can. J. Forest Res. 31: 1579–1593.

Dombeck M.P., Williams J.E. and Wood C.A. 2004. Wildfire policy and public lands: integrating scientific understanding with social concerns across landscapes. Conserv. Biol. 18: 883–889.

Forman R.T.T. 2000. Estimate of the area affected ecologically by the road system in the United States. Conserv. Biol. 14: 31–35.

Fulé P.Z., Heinlein T.A., Covington W.W. and Moore M.M. 2003. Assessing fire regimes on Grand Canyon landscapes with fire-scar and fire-record data. Int. J. Wildland Fire 12: 129–145.

Gelbard J.L. and Belnap J. 2003. Roads as conduits for exotic plant invasions in a semiarid landscape. Conserv. Biol. 17: 420–432.

Gosz J.R., Moore D.I., Shore G.A., Grover H.D., Rison W. and Rison C. 1995. Lightning estimates of precipitation location and quantity on the Sevilleta LTER, New Mexico. Ecol. Appl. 5: 1141–1150.

Graham R.T., McCaffrey S. and Jain T.B. (eds) 2004. Science basis for changing forest structure to modify wildfire behavior and severity. USDA Forest Service General Technical Report RMRS-GTR-120. Fort Collins, CO, USA.

Grigal D.F. 2000. Effects of extensive forest management on soil productivity. Forest Ecol. Manage. 138: 167–185.

Grissino-Mayer H.D. and Swetnam T.W. 2000. Century-scale climate forcing of fire regimes in the American Southwest. The Holocene 10: 213–220.

Guyette R.P. and Dey D.C. 2000. Humans, topography, and wildland fire: the ingredients for long-term patterns in ecosystems. In: Proceedings of the Workshop on Fire, People, and the Central Hardwoods Landscape. USDA Forest Service General Technical Report NE-274. Fort Collins, CO, USA, pp. 28–35.

Heyerdahl E.K., Brubaker L.B. and Agee J.K. 2001. Spatial controls of historical fire regimes: a multiscale example from the interior West, USA. Ecology 82: 660–678.

Keeley J.E. and Fotheringham C.J. 2001. Historic fire regime in southern California shrublands. Conserv. Biol. 15: 1536–1548.

Kemp L.D., Bonham-Carter G.F., Raines G.L. and Looney C.G. 2001. Arc-SDM: ArcView extension for spatial data modelling using weights of evidence, logistic regression, fuzzy logic, and neural network analysis. [Online: (http://ntserv.-gis.nrcan.gc.ca/sdm/).].

Lyford M.E., Jackson S.T., Betancourt J.L. and Gray S.T. 2003. Influence of landscape structure and climate variability on a Late Holocene plant migration. Ecol. Monogr. 73: 567–583.

Malamud B.D., Millington J.D.A. and Perry G.L.W. 2005. Characterizing wildfire regimes in the United States. Proc. Natl. Acad. Sci. USA, 102: 4694–4699.

McGarigal K., Romme W.H., Crist M. and Roworth E. 2001. Cumulative effects of roads and logging on landscape structure in the San Juan Mountains, Colorado (USA). Landscape Ecol. 16: 327–349.

McKenzie D., Gedalof Z., Peterson D.L. and Mote P. 2004. Climatic change, wildfire, and conservation. Conserv. Biol. 18: 890–902.

Mensing S.A., Elston, R.G.Jr., Raines G.L., Tausch R.J. and Nowak C.L. 2000. A GIS model to predict the location of fossil packrat (*Neotoma)* middens in central Nevada. West. N. Am. Nat. 60: 111–120.

Neuenschwander L.F., Menakis J.P., Miller M., Sampson R.N., Hardy C., Averill B. and Mask R. 2000. Indexing Colorado watersheds to risk of wildfire. In: Sampson R.N., Atkinson R.D. and Lewis J.W. (eds), Mapping Wildfire Hazards and Risks. The Haworth Press, New York, NY, USA, pp. 35–56.

Podur J., Martell D.L. and Csillag F. 2003. Spatial patterns of lightning-caused forest fires in Ontario. Ecol. Model. 164: 1–20.

Preisler H.K., Brillinger D.R., Burgan R.E. and Benoit J.W. 2004. Probability based models for estimation of wildfire risk. Int. J. Wildland Fire 13: 133–142.

Prestemon J.P., Pye J.M., Butry D.T., Holmes T.P. and Mercer D.E. 2002. Understanding broadscale wildfire risks in a human-dominated landscape. Forest Sci. 48: 685–693.

Raines G.L. and Mihalasky M.J. 2002. A reconnaissance method for delineation of tracts for regional-scale mineral-resource assessment based on geologic-map data. Nat. Resour. Res. 11: 241–248.

Reed R.A., JohnsonBarnard J. and Baker W.L. 1996. Contribution of roads to forest fragmentation in the Rocky Mountains. Conserv. Biol. 10: 1098–1106.

Sackett S.S. and Haase S.M. 1996. Fuel loadings in southwestern ecosystems of the United States. In: Proceedings of the Symposium on Fire on Madrean Province Ecosystems. USDA Forest Service General Technical Report RM-GTR-289. Fort Collins, CO, USA, pp. 187–192.

Sisk T.D., Prather J.W., Hampton H.M., Aumack E.N., Xu Y. and Dickson B.G. In Press. Participatory landscape analysis to guide restoration of ponderosa pine ecosystems in the American Southwest. Landscape Urban Plan.

Spiegelhalter D.J. 1986. Probabilistic prediction in patient management. Stat. Med. 5: 421–433.

Swetnam T.W. 1990. Fire history and climate in the southwestern United States. In: Krammes J.S. (ed.), Proceedings of the Symposium on Effects of Fire Management of Southwestern Natural Resources. USDA Forest Service General Technical Report RM-191. Fort Collins, CO, USA.

Swetnam T.W. and Baisan C.H. 1994. Historical fire regime patterns in the southwestern United States since AD 1700. In: Allen C.D. (ed.), Fire Effects in Southwestern Forests. Proceedings of the second La Mesa fire symposium. USDA Forest Service General Technical Report RM-GTR286. Fort Collins, CO, USA, pp. 11–32.

Swetnam T.W. and Betancourt J.L. 1990. Fire-southern oscillation relations in the southwestern United States. Science 249: 1017–1020.

Swetnam T.W. and Betancourt J.L. 1998. Mesoscale disturbance and ecological response to decadal climatic variability in the American Southwest. J. Climate 11: 3128–3147.

Thornton P.E., Running S.W. and White M.A. 1997. Generating surfaces of daily meteorology variables over large regions of complex terrain. J. Hydrol. 190: 214–251.

USDA Forest Service. 1999. National fire occurrence data 1986–1996. [Online: (http://www.fs.fed.us/fire/fuelman/).].

USDA Forest Service. 2004. Southwest area wildland fire operations website. [Online: (http://www.fs.fed.us/r3/fire/).].

USDA and USDI [USDA Forest Service and U.S. Department of the Interior] 2000. National fire plan: managing the impact of wildfires on communities and the environment. A report to the President in response to the wildfires of 2000. [Online: (http://www.fireplan.gov)].

Vankat J.L. 1985. Patterns of lightning ignitions in Sequoia National Park, California. In: Proceedings, Symposium, and Workshop on Wilderness Fire USDA Forest Service General Technical Report INT-182, Ogden, UT, USA, pp. 408–411

van Wagtendonk J.W. 1991. Spatial analysis of lightning strikes in Yosemite National Park. In: Andrews P.L. and Potts D.F. (eds), Proceedings of the 11th Conference on Fire and Forest Meteorology. Society of American Foresters, Bethesda, MD, USA, pp. 605–611.

Weatherspoon C.P. 1996. Fire-silviculture relationships in Sierra forests. In: Sierra Nevada ecosystem project: final report to congress. Assessments and scientific management options, Vol. 2, Section 6. University of California, Centers for Water and Wildland Resources, Davis, CA, USA, pp. 1167–1176.

Whelan R.J. 1995. The Ecology of Fire. Cambridge University Press, Cambridge, UK.